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ORIGINAL ARTICLE

Artificial Neural Network Based Model for Forecasting of Inflation in India

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Gour Sundar Mitra Thakur · Rupak Bhattacharyya · Seema Sarkar Mondal

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Abstract Inflation can be attributed to both microeconomic and macroeconomic factors which influence the stability of the economy of any nation. With the raising of recession at the end of the year 2008, world communities started paying much contemplation on inflation and put enormous hard work to predict it accurately. Prediction of inflation is not a simple task. Moreover, the behavior of inflation is so complex and uncertain that both economists and statisticians have been striving to model and forecast inflation in an accurate way. As a result, many researchers have proposed inflation forecasting models based on different methods; however the accuracy is always being a major constraint. In this paper, we have analyzed the historical monthly economic data of India between January 2000 and December 2012 and constructed an inflation forecasting model based on feed forward back propagation neural network. Initially some critical factors that can considerably influence the inflation of India have been identified, then an efficient artificial neural network (ANN) model has been proposed to forecast the inflation. Accuracy of the model is proved to be

Corresponding Author: Gour Sundar Mitra Thakur (✉)
Department of Computer Science and Engineering, Dr. B. C. Roy Engineering College, Durgapur, West Bengal, India
email: cse.gsmt@gmail.com
Rupak Bhattacharyya (✉)
Department of Mathematics, Bijoy Krishna Girls' College, Howrah, West Bengal, India
email: mathsrup@gmail.com
Seema Sarkar Mondal (✉)
Department of Mathematics, National Institute of Technology, Durgapur, West Bengal, India
email: seemasarkarmondal@yahoo.co.in
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satisfactory when compared with the forecasting of some well-known agencies.

Keywords Inflation forecasting · Artificial neural network · Back propagation algorithm

1. Introduction

The term 'Inflation' is derived from the Latin word 'Inflare' which means to blow up or inflate and when used in economic world, it means an expansion of the money supply or an increase in prices. According to Crowther [1], inflation represents a state in which the value of money is falling, i.e., prices are rising. Inflation in a country is generally measured by consumer price index (CPI) of that country. CPI is a comprehensive measure used for estimation of price changes in a basket of goods and services representative of consumption expenditure in an economy. By the term 'Inflation', here, we have actually referred to the inflation measured by CPI. Forecasting of inflation is very crucial because it influences many economic decisions. As mentioned by Croushore [2] investors need accurate inflation forecasts as the returns of stocks and bonds depend on what happens to inflation. In business inflation forecast is required to decide the price of goods and plan production accordingly. Home-owners' decision about refinancing mortgage loans also depend on what they think about future inflation. Noticing this huge influence of inflation in various economic fields, researchers from different backgrounds have proposed many inflation forecasting models since last few decades. Use of soft computing techniques beside various statistical models have also become popular in forecasting inflation due to its capability of handling uncertainty and optimization. Brief explanation of few of those popular statistical models along with their comparison with ANN incorporated models in inflation forecasting are given here.

1.1. Aggregate Supply - aggregate Demand

Aggregate supply - aggregate demand (AS-AD) is a linear macroeconomic model that explains price level and output through the relationship of aggregate demand and aggregate supply. In a report, Benigno [3] discussed that in the AS-AD graphical view, optimal policy simplifies to nothing more than an additional line, inflation targeting, along which the trade-off between the objective of price stability and that of stabilizing the output gap can be optimally exploited. Though it is used by a broad array of economists, in a research Wang et al. [4] demonstrated with the help of experimental results that inflation models obtained by employing ANN techniques have higher accuracy as compared to to AS-AD model.

1.2. Auto Regressive Model

In statistics, auto regressive (AR) model is a representation of a type of random process; as such, it describes certain time-varying processes in nature, economics etc. The AR model for inflation forecasting was proposed by Atkeson et al. [5] on the ground that future inflation is best predicted by current and past inflation. Though this model is widely used in economic decision making, Haider et al. [6] established with the help of experimental results that AR models are more erroneous than ANN based models.

1.3. Moving-average Model

Moving-average (MA) method provides an efficient mechanism for obtaining a value for forecasting stationary time series. The technique is simply an arithmetic average as time passes, with some lag-length determined optimally by an underlying cycle present in the data. The difficulty in using moving averages is their inability to capture the peaks and channels of the series. When the market (actual) data are moving down persistently, the moving average forecast tends to produce over-predicted value and when the market is moving up continually, the moving-average forecast will under-predict the market. Obviously, this method fails to deal with non-stationary data.

1.4. Autoregressive Integrated Moving Average Model

This model is the combination of MA and AR models. Haider et al. [6], as mentioned earlier, established with the help of experimental results that route mean square error (RMSE) of ANNs is also much less than the error when forecasted based on autoregressive integrated moving average (ARIMA) model.

1.5. Vector Auto Regression Model

This model is one of the most successful, flexible, and easy to use models for the analysis of multivariate time series. According to Brandt [7], it is a natural extension of the univariate autoregressive model to dynamic multivariate time series. Binner et al. [8] constructed a non-linear ANN model and proved its efficiency over multivariate vector auto regression (VAR) forecasting models.

From the above discussion, it is obvious that the efficiency of ANN incorporated models in inflation and other economic forecasting is more than that of conventional statistical methods. According to Zhang et al. [9], several distinguishing features of ANNs make them valuable and attractive for a forecasting task. Firstly, as opposed to the traditional model-based methods, ANNs are data-driven self-adaptive methods. Secondly, ANNs can be generalized. Thirdly, ANNs are universal functional approximators and finally, ANNs are nonlinear.

In this proposed work, initially multi-layer feed-forward (MLF) neural network is constructed with back propagation learning algorithm (BPLA) and then historical data of inflation in relation with few critical factors influencing the inflation in India is used to train, validate and test the accuracy of the ANN model. Results are found to be satisfactory when compared with the existing popular models.

The rest of the paper is organised as follows: Section 2 briefly explains the concept of multilayer feed-forward neural network with back-propagation algorithm. The design of the proposed inflation forecasting model is explained in Section 3. Section 4 presents the result analysis of the proposed model. Section 5 provides a comparative study to show the effectiveness and tractability of the proposed approach. Finally, future scope and conclusion of the proposed work are specified in Section 6.

2. Multilayer Feed-forward Neural Network with Back-propagation Algorithm

MLF neural networks with back propagation learning algorithm are the most commonly used neural networks. In MLF, ANN neurones are distributed in ordered layers, where the first is called the input layer and the last is called the output layer. The layers between these two layers are known as hidden layers. Each neurone in any particular layer is connected with all neurones in its immediate next layer. The connection between the ith and jth neurone is characterized by the weight coefficient ω_{ij} and the threshold coefficient of the ith neurone is characterized by the threshold coefficient ϑ_i. The output activity of the ith neurone x_i is calculated by Equation (1) and (2) [10]:

$$x_i = f(\xi_i), \tag{1}$$

$$\xi_i = \vartheta_i + \sum_{j \in \Gamma_i^{-1}} \omega_{ij} x_j, \tag{2}$$

where Γ is a mapping function which assigns each neurone i a subset $\Gamma(i) \subseteq V$ consisting of all ancestors of the given neurone. All predecessors of the given neurone i is represented by the subset $\Gamma_i^{-1} \subseteq V$. ξ_i is the potential of the ith neurone and $f(\xi_i)$ is the transfer function. The threshold coefficient is understood as a weight coefficient of the connection with formally added neurone j, where $x_j = 1$ (bias).

For the transfer function it holds that

$$f(\xi_i) = \frac{1}{1 + \exp(-\xi)}. \tag{3}$$

In supervised adaptation process, the threshold coefficient ϑ_i and weight coefficient ω_{ij} are varied to minimize the sum of the squared differences between the computed and required output values. This is achieved by minimization of the objective function E [10] in (4) as

$$E = \sum_o \frac{1}{2} (x_o - \hat{x}_o)^2, \tag{4}$$

where x_o and $\hat{x}_o$ are vectors composed of the computed and required activities of the output neurones and summation runs over all output neurones o.

In back-propagation algorithm generally gradient descent minimization method is used. Adjustments of the weight and the threshold coefficients are achieved as:

$$\begin{aligned} \omega_{ij}^{(k+1)} &= \omega_{ij}^{(k)} - \lambda \left(\frac{\delta E}{\delta \omega_{ij}} \right)^{(k)}, \\ \vartheta_{ij}^{(k+1)} &= \vartheta_{ij}^{(k)} - \lambda \left(\frac{\delta E}{\delta \vartheta_{ij}} \right)^{(k)}, \end{aligned} \tag{5}$$

where λ is the learning rate ($\lambda > 0$). For the detailed calculation of $\delta E / \delta \omega_{ij}$ and $\delta E / \delta \vartheta_{ij}$ readers can consult [10].

Based on this approach, the derivatives of the objective function for the output layer and then for the hidden layers can be recurrently calculated. This algorithm is known as back-propagation. When a back propagation network is cycled, an input pattern is propagated forward to the output units through the intervening input-to-hidden and hidden-to-output weights. Training of back propagation basically involves feeding training samples as input vectors through a neural network, calculating the error of the output layer, and then adjusting the weights of the network to minimize the error. Each "training epoch" involves one exposure of the network to a training sample from the training set, and adjustment of each of the weights of the network, layer by layer [11].

3. Design of the Proposed Inflation Forecasting Model

The whole design process of the proposed model has been depicted in Fig.1.

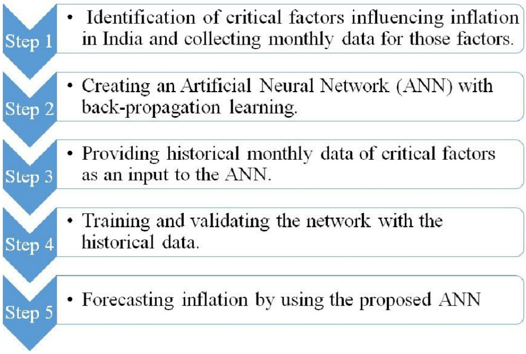

Fig. 1 Design diagram of the proposed inflation forecasting model

3.1. Identification of Critical Factors

Many factors directly or indirectly influence the inflation. Referring the work by Callen and Chang [12] and consulting various domain experts, initially ten critical factors are identified to have considerable impact on the inflation in India. These critical factors are depicted in Fig.2. Brief explanation of these factors are as follows:

3.1.1. Gross Domestic Product

Gross domestic product (GDP) is the broadest quantitative measure of a nation's total economic activity. More specifically, GDP represents the monetary value of all goods and services produced within a nation's geographic borders over a specified period of time.

Dewan et al. [13] found in a sample of 41 middle-income developing countries that inflation is negatively correlated to growth . In case there is a high demand in the goods market, GDP rises; however, this high demand also causes the prices to go up and results inflation. Thus, it may be concluded that there is always a positive correlation between inflation and GDP.

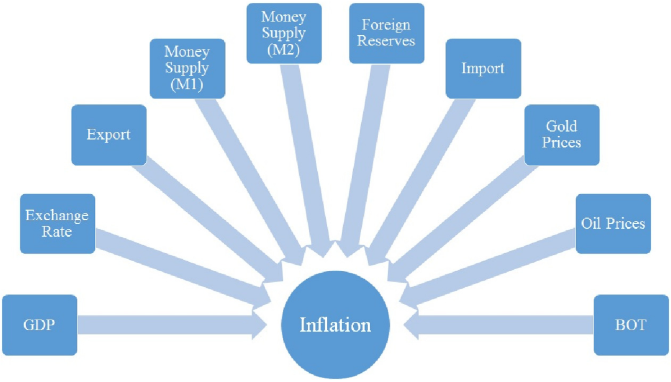

Fig. 2 Critical factors influencing inflation

3.1.2. Exchange Rate

Exchange rate basically is the price of a nation's currency in terms of another currency. An exchange rate has two components, a foreign currency and the domestic currency and it can be quoted directly or indirectly. Campa and Goldberg [14] analyzed the relationship between import price inflation and the exchange rate in several Organization for Economic Co-operation and Development (OECD) countries. Depreciation in the exchange rate has an effect on increasing the price of imports and reducing the foreign price of exports. If the demand of import decreases and the demand of exports increases, the aggregate demand will rise resulting increased inflation. If the economy is already at full employment, prices are pulled upwards.

3.1.3. Exports

Papi and Cheng [15] tried to establish the relationship between various economic variables including exports with inflation. When a country tends to earn maximum foreign exchange and exports more without considering the domestic use of the commodities, it creates a shortage of commodities at home where the price increase. With reference to Pakistan, the failure of export bonus scheme during 1950's is the most common example of this type in cause of inflation.

3.1.4. Money Supply

Kwon et al. [16] tried to establish a linear relationship between inflation and increases in money supply. The higher the money supply, the higher will be the inflation. M_1 is defined as the sum of currency held by the public and transaction deposits at depository institutions (which are financial institutions that obtain their funds mainly through deposits from the public, such as commercial banks, savings and loan associations, savings banks, and credit unions). M_2 is defined as M_1 plus savings deposits and small-denomination time deposits.

3.1.5. Foreign Reserves

In a model, Lin and Wang [17] concluded that when the foreign exchange reserves increases (or the domestic currency depreciates), the inflation rate will be rising while the exchange rate effect is strong. According to the quantity theory of money, the accumulation of reserves might result in inflationary pressures if the resulting monetary expansion is not fully sterilized and exceeds the growth of money demand.

3.1.6. Import

Jonathan McCarthy [18] examined the impact of exchange rates and import prices on the domestic producer price index (PPI) and CPI in selected industrialized economies. If the quantity of imports increases, this will reduce domestic demand and pull inflation. So a rise in import spending, ceteris paribus, reduces consumer spending on domestic goods and therefore reduces domestic inflationary pressure.

3.1.7. Gold Prices

Mahdavi and Zhou [19] discussed that price of gold and inflation is often seen as being connected in a cause and effect relationship. As gold prices move up or down, inflation follows in the same direction.

3.1.8. Oil Prices

Castillo [20] tried to find out the relation between average inflation and oil price volatility. The price of oil and inflation are often seen as being connected in a cause and effect relationship. As oil prices move up or down, inflation follows in the same direction. The reason why this happens is that oil is a major input in the economy and cost of end products rises with rise in the input costs. For example, if the price of oil rises, then it will cost more to make plastic, and a plastic company will then pass on some or all of this cost to consumers, which raises prices and thus inflation appears.

3.1.9. Balance of Trade

Balance of trade (BOT) is defined as difference between export and import of goods and services,

$$BOT = \text{Earnings on export} - \text{Net payment for imports}. \tag{6}$$

During the time when export is more than import, BOT will be favorable. If import is more than export, at that time, BOT will be unfavorable. A country has a trade deficit if it imports more than it exports and the opposite scenario is a trade surplus. The impact of BOT (trade deficit or trade surplus) depends upon the phase from which the economy is passing, i.e., expansion or recession. In a recession, countries like to export more, creating jobs and demand. In a strong expansion, countries like to import more, providing price competition, which limits inflation and, without increasing prices, provide goods beyond the economy's ability to meet supply.

Once the above factors are decided, historical monthly data (2000-2012) of India in favor of these factors and the monthly inflation data are collected from different sources like www.tradingeconomics.com, www.rbi.org.in, www.inflation.eu, www.x-rates.com, and www.indexmundi.com.

3.2. Creating and Training the ANN

As mentioned earlier, in the proposed model, a multi-layer feed-forward neural network with back-propagation learning algorithm is used to predict the inflation in India. Two main stages involved achieving this task are briefly discussed below:

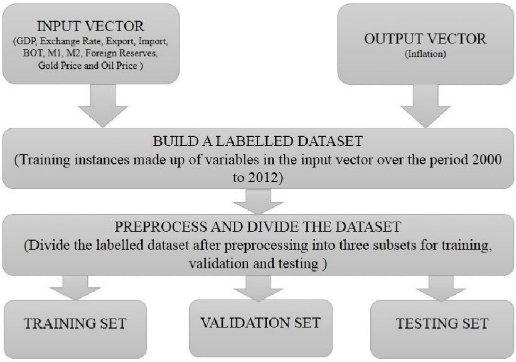

Fig. 3 Collection and distribution of dataset

3.2.1. Collecting and Preparing Data

Historical monthly data of ten factors, as mentioned in Fig. 2, during the period from 2000 to 2012 would generate a vector of size $[10\times156]$ with total of 156 samples. As these ten factors would function as inputs of the proposed ANN, this vector is treated as the input vector. The model is expected to predict monthly inflation of the next year based on the input data provided for the current year. For this reason another vector called target vector of size $[1 \times 156]$ is prepared containing the monthly inflation of the corresponding next year. For example, an input sample of January 2001 in the input vector has the corresponding target value (inflation) of January 2002 in the target vector.

Neural network training can be made more efficient if certain preprocessing steps are performed on the input and output data. As the whole design process is simulated using MATLAB, the two most common functions mapminmax and removeconstantrows are used for input-output data precessing.

Generally, to train multilayer networks the dataset is divided into three subsets. First subset being the training set, is used for computing the gradient and updating the network weight and biases. The second subset, validation set, is used for validation and the third, test set is used for checking test errors in the network. The dividerand function in MATLAB is used to divide the dataset randomly in the ratio of 0.7, 0.15 and 0.15 as training, testing and validation dataset respectively. Fig.3 depicts this whole process.

3.2.2. Training, Testing and Validating the Network

After preparing the dataset, feed-forward network is created and configured with the input layer having 10 input nodes, four hidden layers with 25 neurones and the output layer with one neurone. The network is trained with the well known Levenberg-Marquardt algorithm proposed by Moré and Jorge [21] commonly used as trainlm in MATLAB. Sigmoid function tansig is used in the hidden layer and a linear function purelin is used for the output layer. ANN structure of the proposed model can be visualised through Fig.4.

Training performance of the proposed model is depicted in Fig.5. The training, validation and test curves are very similar. The best validation performance with mean squared error (MSE) 0.836 is found at epoch 18 and the training continued for 6 more iteration before it stopped.

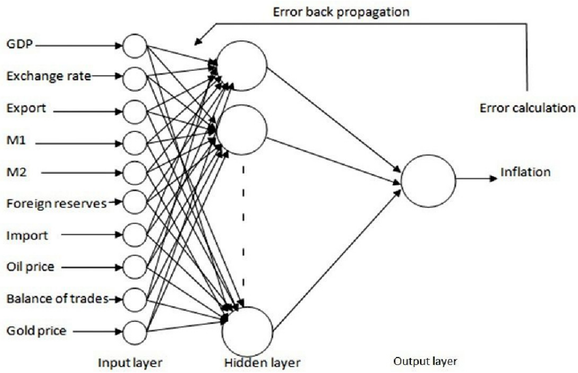

Fig. 4 ANN of the proposed model

Next step in validating the network involves generating the regression plot which shows the relationship between outputs of the network and the targets. If the training was perfect, the network outputs and the targets would be exactly equal, but the relationship is rarely perfect in practice. The regression plot is shown in Fig.6. The three axes represent the training, validation and testing data. The dashed line in each axis represents the optimum result (output = target). The solid line represents the best fit linear regression line between outputs and targets. The R value is an indication of the relationship between the outputs and targets. If $R = 1$, this indicates that there is an exact linear relationship and if R is close to zero, then there is no linear relationship between outputs and targets. The algorithm is terminated according to the early stopping procedure.

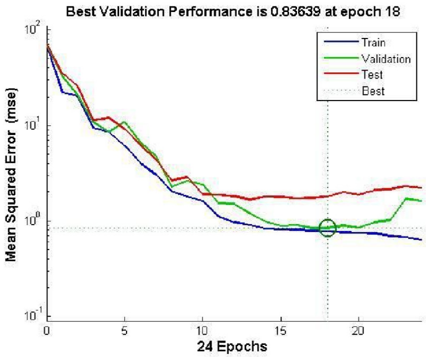

Fig. 5 Training performance of the proposed model

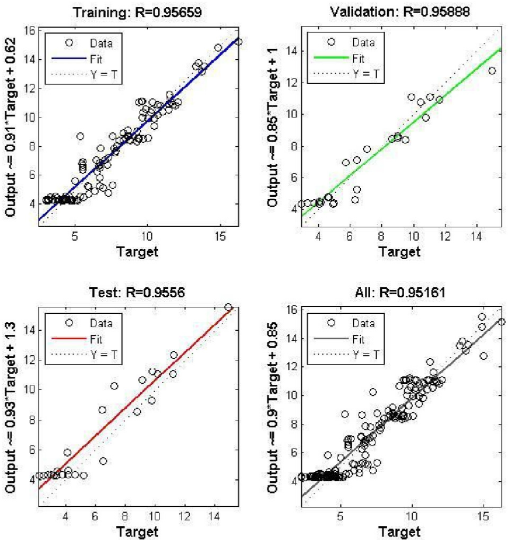

Fig. 6 Training regression of the proposed model

4. Result Analysis

The proposed model is used to predict the monthly inflation in India of 2014 when monthly data of 2013 were provided as input.

Table 1: Actual vs predicted inflation of 2014

Inflation	Actual	Predicted
January, 2014	7.24	10.22
February, 2014	6.73	7.86
March, 2014	6.70	6.90
April, 2014	7.08	7.79
May, 2014	7.02	7.04
June, 2014	6.49	6.23
July, 2014	7.23	7.72
August, 2014	6.75	6.71
September, 2014	6.30	4.58
October, 2014	4.98	5.62
November, 2014	4.12	5.80
December, 2014	5.86	5.26

Table 1 shows the details of actual inflation and the predicted inflation for the year 2014. For example, in August, 2014 actual inflation was calculated as 6.75 and inflation predicted by our proposed model is 6.71. We can see from Fig.7 that the actual inflation and the predicted inflation are very close to each other which clearly establish the reliability and efficiency of the proposed model.

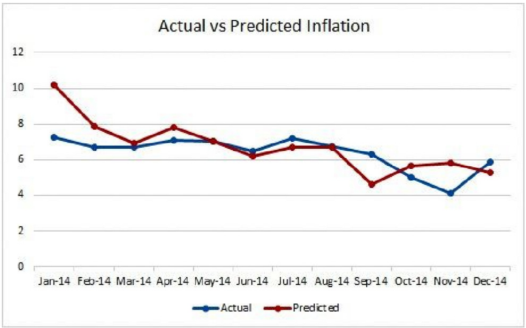

Fig. 7 Actual vs predicted inflation (2014)

The proposed model is also used to forecast the monthly inflation till July, 2015. It is found that the actual average inflation from January, 2015 to July, 2015 is 5.96 where as average inflation for these seven months as per the proposed model is 6.20. Fig. 8 depicts the actual and predicted inflation from January, 2015 to July, 2015.

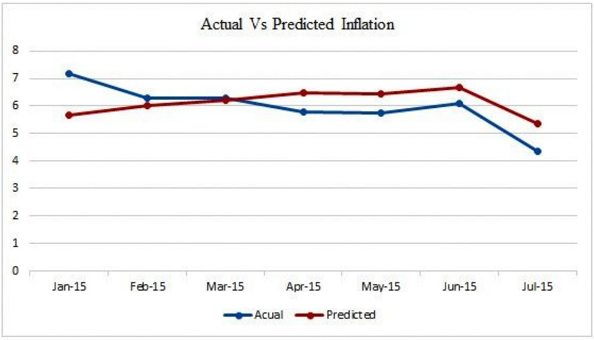

Fig. 8 Actual vs Predicted inflation (2015)

It is clear from the graph that actual and predicted inflation are close to each other in 2015 till July. It again assures the efficiency and applicability of the proposed model.

5. Comparative Study

Many national and international agencies forecast inflation of different nations. We have compared the forecast of our prosed model in India with the three most popular inflation forecasting agencies: Economist Intelligence Unit (EIU) forecast, OECD forecast and International Monetary Fund (IMF) forecast. All these three agencies generally predict average CPI in yearly basis. In Table 2, the actual inflation in 2014 is compared with the forecasts of the proposed model and those of EIU, OECD and IMF.

Table 2: Forecast comparison of different agencies with the proposed model.

Year	Actual inflation	Forecast of the proposed model	EIU forecast	OECD forecast	IMF forecast
2014	6.37	6.73	6.7	7.17	5.99

From Fig.9 clearly that the forecast of the proposed model is closer to the actual inflation than that of OECD and IMF; and it is almost the same as the third one, i.e., EIU. This outcome clearly proves the applicability of the proposed model.

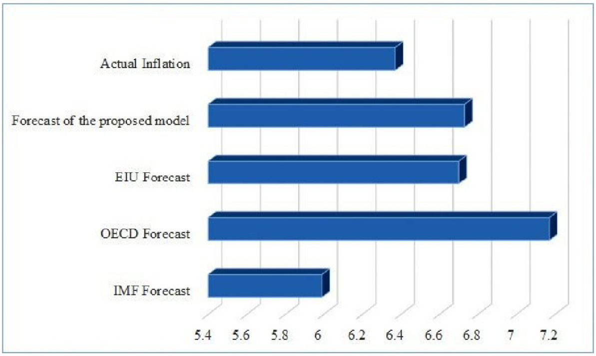

Fig. 9 Comparison of forecasts

6. Conclusion

In this work, a feed-forward ANN is designed with back-propagation learning algorithm to forecast monthly inflation for India on the basis of historical monthly data. Results of the approach are validated by applying statistical evaluations such as MSE. Forecast of the proposed model is compared with that of various other forecasting agencies to illustrate the accuracy and efficiency of the proposed ANN. Though economists attempt to predict future inflation rate by using various theories and practices, it cannot predict inflation rate with 100 percent accuracy. That is because there are so many other factors such as natural disasters, sudden change in weather, government policies, changes in taxation regulations and political decisions in qualitative form, which lead to rise and fall of the inflation rate.

This research is conducted using ten parameters which make significant influence to the Indian inflation rate. The research can be extended by using more variables which would cover wider domain on and of the country's economy. This model is designed typically considering Indian economy, and it can be implemented for any other developed or developing countries also. However, the selection of the influencing factors may vary from country to country.

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